After Aylan Kurdi: How Tweeting about Death, Threat, and Harm Predict Increased Expressions of Solidarity with Refugees over Time

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Abstract

Viral social media content has been heralded for its power to transform policy, but online responses are often derided as ‘slacktivism’. This raises the questions, what drives viral communications, and what is their effect on support for social change? We addressed these issues in relation to Twitter discussions about Aylan Kurdi, a child refugee who died en route to the European Union. We developed a longitudinal paradigm to analyse 41,253 tweets posted by 373 users one week before the images of Aylan Kurdi emerged, the week they emerged, and 10 weeks afterwards – at the time of the Paris terror attacks. Tweeting about death before the images emerged predicted tweeting about Aylan Kurdi, and this, sustained by discussion of harm and threat, predicted the expression of solidarity with refugees 10 weeks later. Results suggest that processes of normative conflict and communication can be intertwined in promoting support for social change.

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On 2nd September 2015, the lifeless body of Syrian three-year old Aylan Kurdi[1] was discovered on a Turkish beach after his family attempted to cross the Mediterranean Sea to flee the Syrian conflict. Within twelve hours, pictures of Aylan Kurdi were retweeted over 30,000 times, reaching at least 20 million people (Vis & Goriunova, 2015). The dissemination of these images has been credited with changing the debate on immigration, and galvanizing a global social movement to address the refugee crisis (Vis & Goriunova, 2015). Within weeks, there were widespread announcements of new public policy responses, with pledges from nations around the world to re-settle 162,151 refugees (Amnesty International, 2016).

Through a longitudinal analysis of language on Twitter, we explore how communicating about threat and harm in the context of the death of Aylan Kurdi was related to later expressions of solidarity with refugees. We suggest that online communications are important for understanding enduring responses to events such as the refugee crisis, because they act as a springboard for mobilizing change on a global scale. Contrary to the 'slacktivism' critique that suggests that low-cost, low-risk online actions foreclose engagement in higher-risk actions by satisfying the motivation to act (Lee & Hsieh, 2013), we show here that communicating online can leave a psychological legacy (Carlisle & Patton, 2013; Schumann & Klein, 2015).

Internet activism is a relatively new phenomenon and much remains unknown about social media's potential for mobilization (Harlow & Guo, 2014; Wojcieszak, 2009). Therefore, psychological science needs new methods to study the psychology of online engagement over time. To this end, we designed a paradigm to enable analyses of the longitudinal relationships between psychological responses to the images of Aylan Kurdi in a large volume of tweets. This approach contrasts with most approaches to understanding variations in activity on Twitter that analyze short term peaks in sentiment or changes in tweet volume across networks or in reaction to events (see Williams & Burnap, 2016). While previous approaches attest to the volume and reach of activity, our approach allows us to make inferences about the form and nature of that activity. We document the psychological processes showing how and why online communications are related to later mobilization.

The Role of Communicating Opinions Online in the Development of Solidarity

Social psychological research has identified mechanisms by which online communications mobilize social movements (Harlow, 2012; Wojcieszak, 2009). McGarty, Thomas, Lala, Smith, and Bliuc (2014) suggested that the growth of mass opposition to government regimes in Tunisia and Egypt in 2010 and 2011 can be explained through the sharing of images of local anti-regime protests from camera phones to videosharing sites and then through satellite television. McGarty and colleagues suggest that this was an example of the process of *opinion-based* social identity formation, where protesters used media to communicate the opinion that the government was an illegitimate outgroup that should be ousted. Similarly, Smith, Gavin, and Sharp (2015) showed that the development of the Occupy Wall Street movement was preceded by Facebook discussions in which supporters of the movement reached agreement on their opinions about how the world should address economic and social grievances (see Castells, 2012, for a detailed account).

These movements reflect what Smith, Thomas, and McGarty (2015) describe as *INN-formation*: the formation of an identity-norm nexus (INN) where people come to understand their commitment to end some unacceptable state of affairs as an aspect of their identity. Smith and colleagues argue that when people perceive a *normative conflict* — a discrepancy between the way the world is (the descriptive norm) and the way they perceive the world ought to be (the injunctive norm) — they are motivated to communicate the discrepancy to change that state of affairs. Communicating about a normative conflict is a central, catalytic process in efforts to promote social change. Aylan Kurdi's image encapsulated the normative conflict that people – children – are harmed while attempting to flee a violent conflict.

The issue of unacceptable harm is of central importance in motivating pro-change responses. According to the theory of moral foundations (Haidt, 2007), harm is one of five broad bases of what people consider to be right or wrong, and focuses attention on concern for others (Graham, Haidt, & Nosek, 2009). Accordingly, we expected that tweeting about Aylan Kurdi, a situation in which a 'universal' societal injunctive norm was violated (children should not be harmed; see Haidt, 2012), would mobilize people to communicate about illegitimate harm and therefore, express solidarity with the victim group. However, during the refugee crisis there were also concerns raised in some quarters about threats from refugees to host communities. Many nations were concurrently on high alert for terrorist attacks. In November 2015, when the Paris terror attacks occurred, it was speculated that the attacks diminished the compassion for refugees (Lyman & Smale, 2015; Wright, 2015). Therefore, we expected that whereas communicating about illegitimate harm would be positively associated with expressions of solidarity with the victim group, communicating about external threats to oneself or others would be negatively associated with solidarity (Huddy & Feldman, 2011; Stephan & Stephan, 2000).

Thus, we predicted that tweeting about Aylan Kurdi would be positively related to expressing solidarity with refugees ten weeks later to the extent that tweets focused on harm (H1) rather than threat (H2). To isolate the variance in solidarity with refugees explained by tweeting about harm and threat (over and above that of pre-existing sympathy with refugees), we controlled for expression of pro-refugee opinions prior to the emergence of the images. It was also the case that the photos of Aylan Kurdi depicted his death, and death thought accessibility can have substantial effects on behaviour (see Burke, Martens, & Faucher, 2010;

McGregor et al., 1998; Vail, Arndt, Motyl, & Pyszczynski, 2012). We therefore controlled for prior talk about death in this study. Doing so allowed us to examine the specific relationship between tweeting about the image of Aylan Kurdi's death and solidarity, whilst controlling for prior pro-refugee opinions and death thought accessibility more generally.

Pilot Study

We used Chorus Tweetcatcher 1.3 software (Brooker, Barnett, & Cribbin, 2016) to retrieve publicly available Twitter data via the Twitter Search API. We then used Linguistic Inquiry and Word Count (LIWC2015) software (Pennebaker, Boyd, Jordan, & Blackburn, 2015) to establish the proportion of tweets by each user at each time point that contained words in the dictionary categories. To establish the proportion of words that contained pro-refugee content, we created a custom LIWC dictionary. First, in a pilot study described below, we established that the custom dictionary captured pro-refugee content, rather than refugee content in general.

Method

Participants and design. We conducted an a priori power analysis that established that the sample size required for $d = 0.50$ was 54 participants (to detect significance at $p < .05$ in a one sample t-test; Faul, Erdfelder, Lang, & Buchner, 2007). We recruited 59 participants (85% female), via a post advertising the survey on Twitter and from the Department of Psychology Research Participation Scheme for first year undergraduates at a UK university. All participants were Twitter users. Eighty-eight percent were UK residents. Via an online survey, they rated each of the pro-refugee hashtags and words/phrases in Table 1 on a scale of 1 to 7, whereby 1 = *Not at all pro-refugee*, 4 = *neutral*, and 7 = *Completely pro-refugee*. These hashtags and words/phrases were selected through using Chorus' TweetVis visual analytics suite (Brooker et al., 2016), that identified the most frequently used relevant hashtags and words associated with the broad hashtag #refugees.

Results

We conducted a series of one-sample *t*-tests to compare the mean score for each key term against the neutral point of the scale (‘4’; see Table 1). All of the terms were significantly associated with being pro-refugee with the exception of ‘refugee’, $t(53) = 0.87$, $p = .39$, $d = 0.19$, ‘refugeescrisis’, $t(55) = 1.67$, $p = .10$, $d = 0.22$, ‘roeszke’ (a refugee camp and border crossing into Hungary from Serbia that was widely discussed in 2015) , $t(53) = -0.79$, $p = .44$, $d = 0.08$, ‘refugeesgr’, $t(52) = 1.79$, $p = .08$, $d = 0.25$, ‘syrianrefugees’, $t(54) = 1.15$, $p = .26$, $d = 0.16$, ‘refugeeconvoy’, $t(55) = 0.67$, $p = .51$, $d = 0.09$, ‘soseurope’, $t(55) = 0.16$, $p = .87$, $d = 0.02$, ‘notinmyname’, $t(54) = 0.96$, $p = .34$, $d = 0.13$, and ‘islamophobia’, $t(54) = -1.23$, $p = .22$, $d = -0.17$. An initial principal axis factor analysis with direct oblimin rotation indicated that the top two factors differentially represented Refugee Talk and Pro-Refugee Talk, (the eigenvalues were $\lambda = 6.32$ and $\lambda = 2.87$ respectively, together explaining 36% of the variance). The above terms loaded onto the former rather than the latter factor, and were therefore omitted from the pro-refugee custom dictionary. The terms, ‘UKhousing’, $t(54) = -3.49$, $p = .001$, $d = -0.47$, and ‘fortresseurope’, $t(54) = -2.43$, $p = .02$, $d = -0.33$, were significantly negatively associated with Pro-Refugee Talk. Therefore, these terms were also omitted from the dictionary. Scores for the remaining 12 key terms were entered into a second factor analysis. The eigenvalue for the Pro-Refugee Talk factor was $\lambda = 4.28$ (explaining 33% of the variance). The terms formed a reliable measure, $\alpha = .83$. Therefore, for the purposes of our main study, we created a custom dictionary to capture pro-refugee talk that contained these 12 terms plus variants thereof (see Appendix A for a full list of items).

Table 1

Validation of Key Terms in Pro-Refugee Custom Dictionary (*N* = 59)

Term	*M*	*SD*	Loading onto Pro-Refugee Talk	*T*	Mean difference from neutral mid-point of scale	*d*	95% Confidence interval of the difference	
							Lower	Upper
Refugeeswelcome	6.40	1.08	.54	16.45	2.40	2.22	2.11	2.69
Welcome	5.04	1.67	.78	4.61	1.04	0.62	0.59	1.49
Supportrefugees	6.21	1.04	.58	15.94	2.21	2.13	1.94	2.49
Supportmigrants	5.73	1.52	.71	8.42	1.73	1.14	1.32	2.14
Pray	5.16	1.56	.57	5.57	1.16	0.74	0.74	1.58
Prayforsyria	5.73	1.21	.59	10.68	1.73	1.43	1.41	2.06
Shameoneurope	5.11	1.69	.61	4.90	1.11	0.66	0.65	1.56

Wehaveroom	6.21	1.07	.53	15.43	2.21	2.07	1.93	2.50
Withsyria	5.84	1.01	.35	13.43	1.84	1.82	1.56	2.11
Wecandobetter	5.48	1.34	.58	8.31	1.48	1.10	1.12	1.84
Soukforsyria	4.67	1.36	.44	3.60	0.67	0.49	0.30	1.04
Solidarity	5.14	1.51	.47	5.68	1.14	0.75	0.74	1.55

Main Study

Method

Data collection. Using a series of keyword searches in Chorus, we harvested tweets between the dates of 6th September 2015 (the week following the first tweet containing the image of Aylan Kurdi) and 30 November 2015. Using Twitter's Search API we could harvest a user's past 3200 tweets along their user timeline and one week of tweets for keyword searches. Initial search terms were: #refugeescrisis, #migrantcrisis, #AylanKurdi, #Aylan_Kurdi, migrant crisis, Syria, refugees, #Syrianrefugees, #refugees; and variants thereof. To evolve the search with the changing narrative around the situation, we included the additional search terms: #savethechildren, helpiscoming, #Hungary. These searches yielded 35,537 tweets by 22,212 distinct user IDs.

We next identified a subset of users for whom tweets existed before and after the publication of the images of Aylan Kurdi. These users met the following criteria: a) their profile indicated that they were located in the UK, b) they had tweeted at all three time points, and c) they had tweeted about refugees using the hashtags described above. To select this sample, we used TweetVis to compile a list of all distinct user IDs within the full dataset who were located in the UK. Restricting the sample yielded a European, almost exclusively English language tweet corpus without the need to remove tweets in languages other than English (many European Twitter users tweeted both in their national language and in English on this topic). Within the overall dataset, 11,308 tweets originated from the UK. To harvest the tweets of users in the UK that were sent prior to the emergence of the images of Aylan Kurdi, we conducted an additional set of searches using the UK-based usernames in this original dataset. These searches harvested each user's previous tweets up to one week before the images of Aylan Kurdi were first publicized. Overall, the longitudinal dataset contained 41,253 tweets by 373 users in three week-long time periods.

Time 1 (T1). In the seven day period between 26th August 2015 and 1st September 2015, we harvested the data from 459 unique user names with UK locations. This dataset included 23,633 tweets. To control for authors' linguistic style (Milhail, Ilya, & Ieee, 2014) and to ensure we analyzed only the sampled users' own opinions, we used Chorus' automated text analysis to classify and remove re-tweets (messages originating from another user that a user chose to retransmit). Overall, 9,987 (42%) of the tweets were retweets. Removing these retweets resulted in a final T1 dataset that included 13,646 tweets and 431 users (the mean original tweet frequency per username was 31.59).

Time 2 (T2). The images of Aylan Kurdi first emerged in the dataset on 2nd September 2015. During the seven day period between 2nd and 8th September 2015, all of the T1 users tweeted. This dataset included 20,703 tweets. Overall, 7,215 (34.85%) of the tweets were retweets. Removing these retweets resulted in a final T2 dataset that included 13,488 tweets and 422 users (i.e., 9 of the 431 T1 users only re-tweeted at T2).

Time 3 (T3). Time 3 was ten weeks after T2, and immediately following the Paris terror attacks (12th November), in the seven day period between 13th and 19th November 2015. We chose this time point because it was popularly assumed that the terror attacks – that were erroneously rumoured to be perpetrated by refugees – had reduced compassion for refugees (Lyman & Smale, 2015; Wright, 2015). If expressions of solidarity at this time were positively related to earlier tweets about Aylan Kurdi despite the salience of terrorism, this would be a pertinent response to the slacktivism critique (i.e., because tweeting about Aylan Kurdi's images was associated with later public expressions of solidarity with refugees despite the threat from terrorism). This dataset included 20,501 tweets. Overall, 6,382 (31.12%) of the tweets were retweets. Removing these retweets resulted in a final T3 dataset that included 14,119 tweets and 373 users (all of whom had tweeted at T1 and T2).

Analytic Strategy

The purposes of our analyses were a) to explore the relationship between communicating about Aylan Kurdi at T2 and expressing solidarity with refugees at T3, controlling for the expression of pro-refugee opinions and communications about death (in general; death thought accessibility) at T1; and b) to explore the processes by which communicating about Aylan Kurdi at T2 was related to expressing solidarity with refugees at T3. Thus, our analytic strategy aimed to identify content that could explain why communicating about Aylan Kurdi at T2 was connected to the expression of solidarity with refugees ten weeks later, at T3, in the context of the Paris terror attacks, whilst accounting for earlier expressions of pro-refugee sentiment and discussions about death in general at T1. To do this, each user's tweets at each time point were combined into a single unit of observation for analyses (controlling for the number of tweets). Using LIWC2015, we then established the proportion of words by each participant at each time point that appeared in the standard and custom dictionary word categories (including the death category, e.g., 'bury', 'coffin', 'kill', to control for the salience of death before the images emerged; and the affiliation category, e.g., 'ally', 'friend', 'social', because it was the closest LIWC category to the concept of social identification with a group; see Pennebaker, et al., 2015). To index the proportion of words by each participant relating to harm and loyalty, we used the moral foundations dictionary created by Graham, Haidt, and Nosek (2009).

We created additional custom LIWC dictionaries to capture collective action content and threat content (see Appendix A for the full list of terms). One of the current authors and an independent person generated lists of words for each category based on common English terms and common terms used in social psychological treatments of the two constructs. The independent lists were merged after discussion and then assessed in a sample of 14,395 English language tweets (with spam and non-text tweets removed) drawn from tweets that included the hashtag #refugees in mid-2016 (collected independently of this study). The mean proportion of threat words in the #refugees corpus was $M = 0.17$ words, $SD = 1.00$. The custom threat category was correlated .36 with risk in the standard LIWC2015 dictionary, which is noteworthy as perceptions of risk are central to the perception of threat (Huddy & Feldman, 2011). We concluded that this measure was related to, but not redundant with, risk. Collective action was more prevalent in the corpus with a $M = 0.84$, $SD = 2.26$, and was correlated .13 with affiliation (the closest existing, but clearly distinct, construct in the standard LIWC2015 dictionary).

We further validated the threat and collective action dictionaries using Smith, Gavin, and Sharp's (2015) dataset of posts and comments on the #OccupyWallStreet Facebook event page. The mean proportion of collective action words in the #OccupyWallStreet corpus was 2.11 ($SD = 5.04$) and the mean proportion of threat words was 0.06 ($SD = 0.54$). Collective action and threat were not correlated, $r(4552) = -.01$, $p = .50$.

In Appendix B, we include T1 correlations from the present study. Again, threat and collective action were not significantly correlated with each other, suggesting that they are independent constructs. Furthermore, threat was positively correlated with T1 risk and T1 harm. Collective action was positively correlated with T1 affiliation and T1 anger (both LIWC2015 standard dictionary categories). The latter result is important as group-based anger, reflecting grievances about unjust circumstances, is an antecedent of collective action (van Zomeren, Postmes, & Spears, 2008). Taken together, this suggested that content pertaining to collective action was more relevant to mobilization than content related to threat.

Next, we constructed a latent Time 3 variable as our dependent variable to capture solidarity with refugees. This latent variable included the dictionary categories for pro-refugee talk, collective action, loyalty, and affiliation (Figure 1). Then, we conducted path analyses to examine the fit of the hypothesized model (Figure 2) using the Maximum

Likelihood procedure in AMOS v.18.0 (Byrne, 2009). An a priori power analysis established that the sample size required for $d = 0.50$ was 86 observations (to detect significance at $p < .05$ in a regression model with 15 predictors; Faul et al., 2007). Missing values were estimated and replaced using the expectation-maximization algorithm in SPSS. This enabled us to examine the indirect relationships between discussion of Aylan Kurdi and expression of solidarity with refugees through discussion of issues relating to harm and threat, controlling for Time 1 expression of pro-refugee opinions, and discussion of death-related issues (as a control for death-thought accessibility).

To test for indirect effects, we calculated the standardized bias-corrected bootstrap confidence intervals (for details of this bootstrapping procedure, see Cheung & Lau, 2008) using the unbiased estimates of mediation effects provided by the path model. The models' goodness of fit was tested by using the chi-square ratio, the goodness of fit index (*GFI*; Tanaka & Huba, 1985), the root mean square error of approximation (*RMSEA*; Browne & Cudeck, 1993), and standardized *RMR* (Hu & Bentler, 1999).

Results

Preliminary Analyses

Means and standard deviations of the LIWC dimensions, custom dimensions, and additional metrics are in Table 2. Correlation coefficients to assess the zero-order relationships between the variables in the hypothesized model, including volume of tweets at each time point, are available in Table 3. At T1, the most frequently used hashtags were #refugees (89), #refugeecrisis (52), #Syria (46), and #lesbos (40). At T2, the most frequent hashtags were: #refugeeswelcome (280); #refugees (261); #refugeecrisis (169); and #Syria (154). At T3 the top hashtags were #parisattacks (459); #paris (369); #isis (64); #Syria (61); #refugees (43). This demonstrates that discussions about refugees occurred frequently at each time point, and although the Paris attacks were very widely discussed at Time 3, discussion about refugees was still present.

Main Analyses

Indexing solidarity with refugees. We conducted a confirmatory factor analysis to verify the factor structure of the proposed latent variable for Solidarity (with refugees) that contained the following T3 word categories as observed variables: loyalty, pro-refugee, collective action, and affiliation (Figure 1). The unstandardized pathway between loyalty and Solidarity was constrained to 0.70 to achieve identifiability. Results indicated that the latent variable fitted the data adequately, χ^2 (2) = 16.99, p < .001, *GFI* = .98, *SRMR* = .05, *RMSEA* = .13. All of the observed variables loaded significantly onto the factor at $p \leq .01$.

Test of hypothesized model. Fit indices for the hypothesized model, controlling for volume of tweets sent at each time point, were, χ^2 (49) = 190.01, p < .001, *GFI* = .93, *SRMR* = .06, *RMSEA* = .08 (suggesting adequate, but not good, fit). Examination of the modification indices suggested that addition of paths between T1 pro-refugee and T3 Solidarity β = .21, p = .002; and between T3 threat and T3 harm β = .34, p < .001 would improve fit. Indeed, addition of these paths improved the fit of the model, χ^2 (47) = 126.28, p < .001, *GFI* = .96, *SRMR* = .06, *RMSEA* = .06. Taken together, these fit indices suggested that the relationships explained a significant amount of variance in the data (Figure 2). There was a significant positive relationship between the T1 death category and the T2 Aylan Kurdi category, β = .15, p < .001. Therefore, people who mentioned death at T1 (before Aylan Kurdi's death) were more likely to tweet about Aylan Kurdi the following week. However, the relationship between the T1 pro-refugee category and the T2 Aylan Kurdi category was not significant, β = .05, p > .250, indicating that there was no association between pro-refugee talk at T1 and posting about Aylan Kurdi a few days later. However, as expected, there was a significant positive relationship between talking about Aylan Kurdi at T2 and discussing harm at T3, β = .19, p = .001, and between discussing harm at T3 and Solidarity at T3, β = .25, p = .001 (H1).

Table 2

Means and Standard Deviations for LIWC2015 Dimensions and Metrics

LIWC Dimension	T1 (*n* = 431)		T2 (*n* = 422)		T3 (*n* = 373)	
	Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*
Word count	524.08_a	711.12	509.86_a	649.89	635.77_b	718.31
Total tweets	31.66_a	53.16	26.93_b	35.90	32.00_a	38.84
Total re-tweets	1681.86_a	11298.86	4608.61_b	24041.13	–	–
Aylan Kurdi	–	–	0.12_a	0.46	0.01_b	0.04
Pro-refugee	0.06_a	0.32	0.81_b	1.55	0.12_c	0.28
Threat	0.07_a	0.22	0.15_b	0.40	0.06_a	0.13
Collective action	0.64_a	0.72	0.76_b	0.84	0.64_a	0.71
Harm	0.14_a	0.44	0.19_a	0.38	0.36_b	0.52
Loyalty	0.14_a	0.27	0.16_a	0.34	0.17_a	0.31
Affiliation	1.94_a	1.64	2.04_a	1.69	1.86_a	1.28
Death	0.23_a	0.48	0.33_b	0.54	0.37_b	0.48

Means on the same row with different subscripts differ at $p < .05$.

All means are expressed as percentage of total words used in each sample.

Table 3

Zero-order Correlations, Means, and Standard Deviations

		M	*SD*	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.
1.	T1 death	0.24	0.62	–												
2.	T1 pro-refugee	0.06	0.32	.31**	–											
3.	T2 Aylan Kurdi	0.13	0.47	.16**	.10*	–										
4.	T2 threat	0.15	0.42	.06	.02	.15**	–									
5.	T3 harm	0.36	0.50	.21**	.10	.23**	.21**	–								
6.	T3 threat	0.06	0.13	.10*	.10	.06	.17**	.36**	–							
7.	T3 Solidarity (with refugees)	0.74	0.46	.10**	.06	.03	.15**	.16**	.08	–						
8.	T3 pro-refugee	0.18	0.37	.07	.26**	-.06	.004	.13**	.11**	–	–					
9.	T3 loyalty	0.17	0.29	-.004	.07	.00	.19**	.17**	.15**	–	.21**	–				

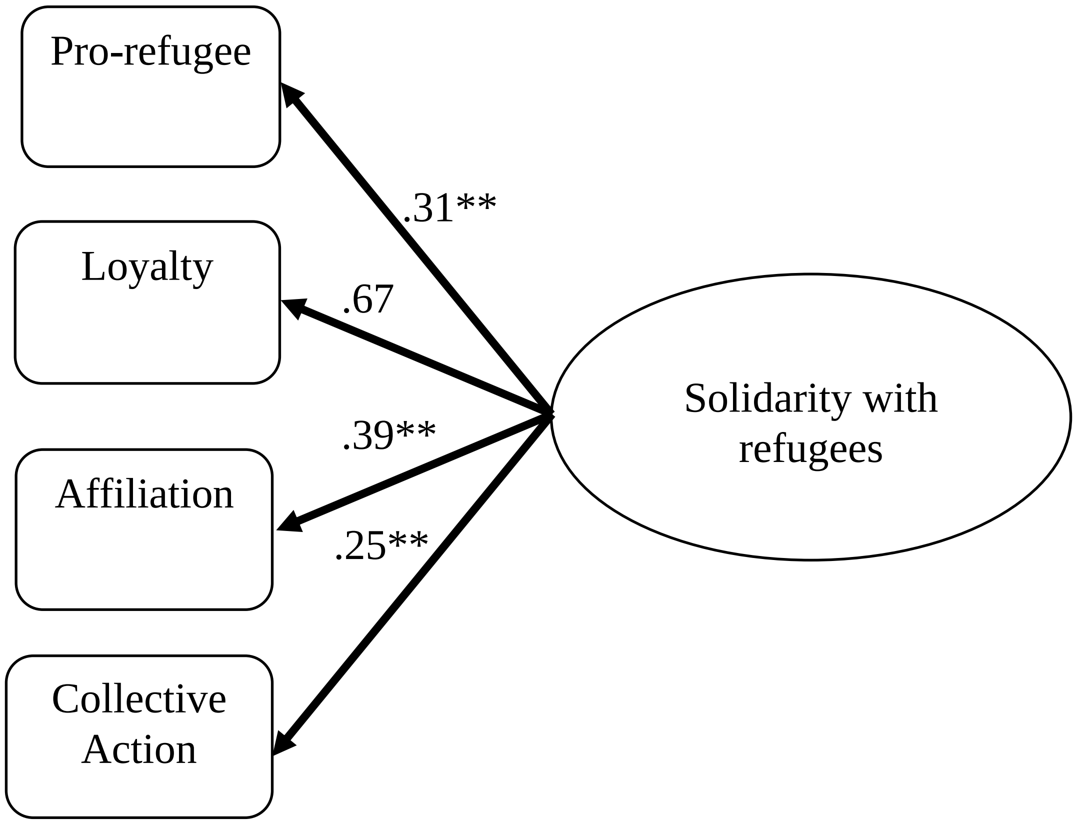
10.	T3 affiliation	1.92	1.31	.08	-.02	-.01	.10	.04	-.02	–	.01	.28**	–			
11.	T3 collective action	0.67	0.77	.09	.06	.09	.09	.18**	.07	–	.09	.09	.17**	–		
12.	T1 volume of tweets	31.61	53.11	.01	-.02	-.05	.03	.07	.03	-.002	.01	-.02	-.03	.02	–	
13.	T2 volume of tweets	26.90	35.87	.03	.02	-.04	.03	.08	.09	.03	-.03	-.01	-.03	.07	.46**	–
14.	T3 volume of tweets	32.00	38.84	.04	.03	.03	.05	-.02	.09	.07	-.03	.08	.05	.05	.04	.04

Time 1 (T1) *n* = 431; Time 2 (T2) *n* = 422; Time 3 (T3) *n* = 373

*p < .05, **p < .01

Figure 1

Confirmatory Factor Analysis of Latent Factor for Solidarity with Refugees at Time 3

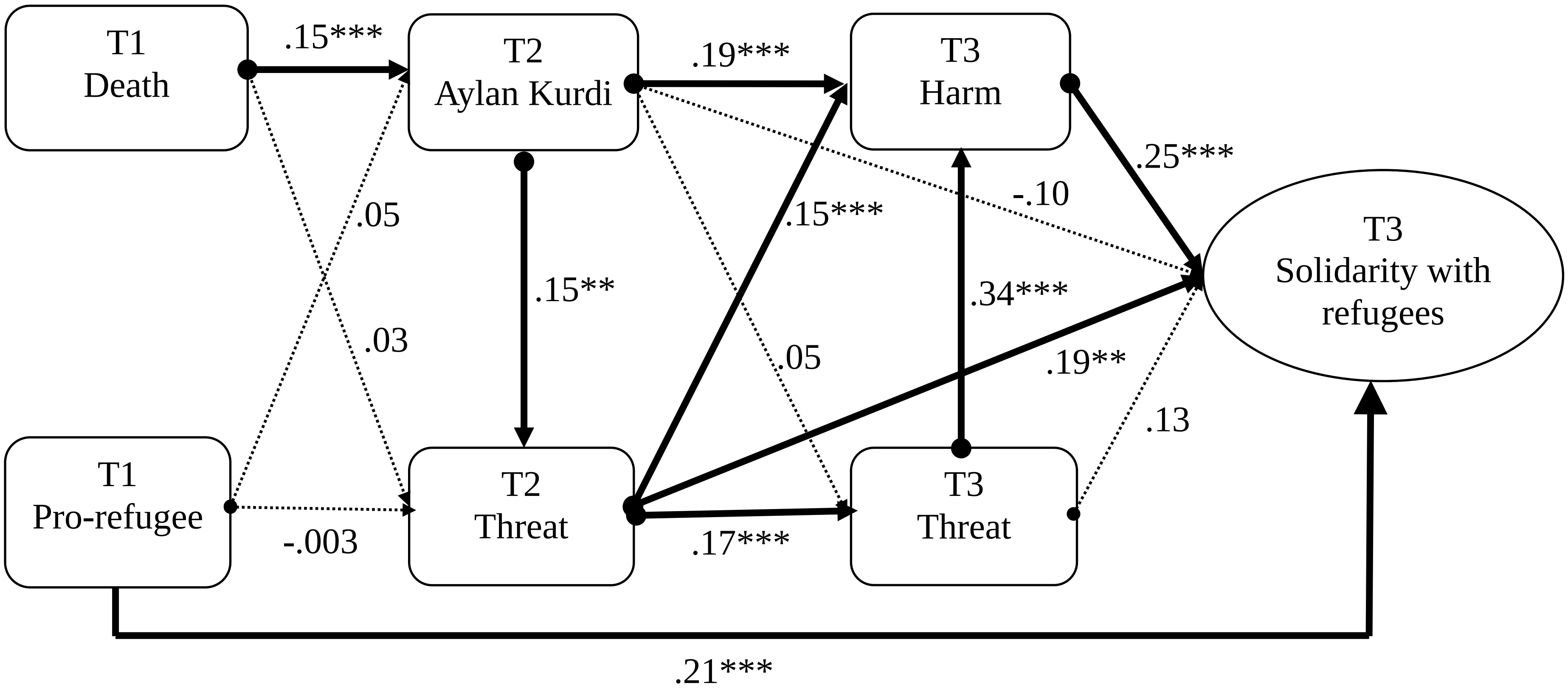


***p* < .01; Standardized coefficients appear on paths. The unstandardized coefficient for loyalty was constrained to 0.7 to enable identifiability.

Missing values were estimated and replaced via expectation-maximization

Figure 2

Test of Hypothesized Model



***p* < .01, ****p* < .001

T1 = Time 1; T2 = Time 2; T3 = Time 3

Standardized beta coefficients appear on paths

A dotted line indicates a non-significant path

Analyses control for volume of tweets at each time point

Missing values were estimated and replaced via expectation-maximization

Model includes correlations between T1 variables

Unexpectedly, there was a significant positive relationship between discussing Aylan Kurdi and threat at T2 $\beta = .15$, $p = .002$, and there was a positive relationship between discussing threat at T2 and Solidarity at T3, $\beta = .19$, $p = .008$. At T3, discussing threat did not predict Solidarity, $\beta = .13$, $p = .08$. We had expected that expression of threat would be negatively associated with tweeting about Aylan Kurdi and with Solidarity (H2) due to the narratives present at the time that linked refugees with threat to host communities. Instead, these results suggested that the threat expressed may not have reflected perceived threat from refugees; rather, it may have reflected threat to refugees. Therefore, we conducted a further analysis to explore the attributions of threat across waves.

We manually coded a subset of tweets containing threat words at each time point (Table 4). In those T1 tweets that contained threat content, the percentage of threat words within the tweets ranged from 3.45 (minimum) to 14.29 (maximum), with a median of 5.26. We selected 25 tweets randomly from each quartile. Two coders independently coded each tweet, and a third coder resolved any disagreements. For the purpose of establishing the threat attributions made about refugees – that is, whether the tweets focused on the threat to refugees posed (for example) by perilous journeys and murderous regimes, versus threat perceived to be posed by refugees to host communities, we used five coding categories: a) threat to refugees; b) threat from refugees; c) threat from terrorism; d) mention of the refugee/migrant “crisis” with unattributed threat; and e) none of the above. For 10 of the 300 tweets, two different codes were applied to a single tweet (meaning that the percentages in Table 4 for each wave sum to greater than 100%). We computed Siegel and Castellan’s (1988) kappa for each coder pair then averaged it to provide a single index of inter-rater reliability. The resulting kappa for T1 indicated substantial agreement, $\kappa = 0.87$ (Landis & Koch, 1977).

At T1, in 11% of the tweets the context of the threat was a threat experienced by refugees, and 24% mentioned the migrant or refugee crisis without a direct attribution of threat. At T2 (κ = 0.70), the percentage of threat words within the tweets ranged from 3.33 to 20.00 with a median of 5.26. In 27% of the tweets, the context of the threat was a threat experienced by refugees. In only 8% of tweets was threat attributed to refugees or from terrorism. There was a significantly greater number of tweets about threat experienced by refugees than threat from refugees, $\chi^2(1) = 20.12$, $p < .001$. At T3 (κ = 0.84), the percentage of threat words within the tweets ranged from 3.70 to 20.00, also with a median of 5.26 (by coincidence, various 19 word tweets containing one threat word at each time point − hence containing 5.26% threat content − appeared at the median position at all three waves). The mode at T1 and T3 was 5% threat, (1 threat word within a 20 word tweet) and 5.56% at T2 (1 threat word within an 18 word tweet). At T3, none of the tweets referred to a threat experienced by refugees, but 32% of tweets mentioned threat from terrorism.

Table 4

Content Analysis of Threat Attributions

			%	
Code		T1	T2	T3
1	Threat to refugees	11	27	0
2	Threat from refugees	3	4	3
3	Threat from terrorism	1	4	32
4	Mention of refugee/migrant “crisis” with unattributed threat	24	40	15
5	None of the above	63	27	56

There was no direct association between discussing Aylan Kurdi at T2 and Solidarity ten weeks later, β = -.10, p = .14. However, the results of bias-corrected bootstrapping with 2000 resamples (Table 5) is consistent with discussion of harm at T3 and threat at T2 (but not at T3) mediating the relationship between discussion of Aylan Kurdi at T2 and Solidarity at T3. In addition, the indirect effect of discussing threat at T2 on Solidarity at T3 was significant, with discussion of harm at T3 but not threat at T3 mediating this relationship. However, T1 discussions of death did not have an indirect effect on T3 Solidarity, suggesting that death thought accessibility at T1 cannot explain the observed relationships. Similarly, expressing pro-refugee statements at T1 did not have an indirect effect on expressing Solidarity at T3.

Table 5

Confidence Intervals for Indirect Effects

Indirect Effect	Mean β	95% confidence interval
Overall effect: T2 AK to T3 solidarity	.05*	.03, .08
T2 AK to T3 Solidarity through T2 threat	.02*	.003, .04
T2 AK to T3 Solidarity through T3 threat	.01	-.003, .03
T2 AK to T3 Solidarity through T3 harm	.03*	.01, .06
Overall effect: T2 Threat to T3 Solidarity	.05*	.02, .08
T2 threat to T3 Solidarity through T3 threat	.02	-.002, .04
T2 threat to T3 Solidarity through T3 harm	.04*	.01, .07
Overall effect: T1 death to T3 Solidarity	.003	-.01, .02
Overall effect: T1 pro-refugee to T3 Solidarity	-.001	-.02, .02

*p < .05

Number of resamples = 2000

Missing values were estimated and replaced via expectation-maximization

Analyses control for volume of tweets at each time point

AK = Aylan Kurdi; T1 = Time 1; T2 = Time 2; T3 = Time 3

Discussion

Tweeting about the death of Aylan Kurdi predicted expressing solidarity with refugees ten weeks later to the extent that tweets focused on threat at the time the images emerged, and harm at the time of the Paris terror attacks. This refutes the suggestion that engagement through social media need be a tidal wave of reaction that quickly subsides (cf. Morozov, 2009). Rather, communicating opinions online can be associated with substantive social and psychological changes (Harlow, 2012; McGarty et al., 2014; Smith, Gavin, & Sharp, 2015; Thomas et al., 2015; Wojcieszak, 2009). Thus, accounts of slacktivism are overly simplified; they do not take into account the way in which communicating opinions about social issues and events relate to the nature of later communications. Specifically, our results highlight the relationships between communicating about death, harm, and threat, and solidarity with an outgroup facing those threats.

We found a positive, direct relationship between the expression of pro-refugee opinions at T1 and T3 solidarity. When controlling for this relationship, tweeting about Aylan Kurdi at T2 was positively related to expressing solidarity with refugees ten weeks later to the extent that discussions expressed a sense of harm. Therefore, in line with H1, we suggest that this is because awareness of harm focused attention on concern for refugees (Graham et al., 2009) and predicted increased expressions of solidarity (Smith, Thomas, & McGarty, 2015).

Intriguingly, expressing pro-refugee opinions at T1 was not related to tweeting about Aylan Kurdi at T2. This suggests that the Aylan Kurdi situation not only moved people who were already pro-refugee or had “prosocial values”, but also motivated those less involved.

This supports our contention that Aylan Kurdi's images violated a 'universal' injunctive norm and caused a normative conflict (Smith, Thomas, & McGarty, 2015).

The T3 data were collected just after the Paris terror attacks, when discussions about the ongoing Syrian refugee crisis were intermingled with conversations about terrorism. This timing is significant because tweeting about Aylan Kurdi was positively associated with tweeting about threat at T2, and there was a direct, positive relationship between threat at T2 and Solidarity at T3, but not between tweeting about threat at T3 (the time of the terror attacks) and Solidarity at T3. Therefore, rather than polarizing people against refugees (H2), communicating about threat was associated with positivity towards the group. At T2, the threat communicated focused on threat to refugees, rather than threat posed by refugees. However, at T3 (when there was no relationship between communicating about threat and Solidarity), the threat communications focused on threat from terrorism. Therefore, only when threat communications focused on threat to vulnerable outgroups were they associated with solidarity.

People who tweeted about death before the images emerged were more likely to tweet about Aylan Kurdi. This effect was apparent even when controlling for pro-refugee sentiment. It may be that people who tweeted about death before the images emerged were more able to relate to the situation of refugees such as Aylan Kurdi and were therefore more likely to tweet about it. Indeed, Boyd, Morris, and Goldenberg (2017) found that in the presence of mortality salience, people who were open to experience were insulated from defending their world views. While one way to reduce the anxiety potentially associated with awareness of death is to avoid discussions of death (see Becker, 1973), people who were already tweeting about death would be more likely to have the resources to buffer against anxiety induced by graphic images of death, and would therefore be more likely to tweet about Aylan Kurdi. This positive relationship between communicating about death and about images of the death of vulnerable others, and in turn the relationship with intergroup solidarity, presents an intriguing avenue for future research on improving intergroup relations.

We adopted a novel methodology to study these processes in a large dataset, incorporating the strengths of quantitative analyses of observed communications with a commitment to examining the content of those communications. Much remains unknown about the extent to which social media communications can affect social change, and how they do so. By deploying these novel longitudinal methods, we were able to demonstrate that online communications involve a psychological doubling down: discussion of harm and threat in combination with the expression of a normative conflict (Smith, Thomas, & McGarty, 2015) is associated with mobilization potential.

There were major policy changes in many nations shortly after the images emerged (Amnesty International, 2016). Political actors respond to popular public opinion expressed through social media, so it is important to understand online activism in its own terms, regardless of whether that activism transfers to offline domains. Not all online engagement necessarily results in psychological change and we did not consider all forms of online engagement (e.g., re-tweeting). Future research could examine whether the psychological responses observed here apply in the context of less effortful communications such as re-tweeting and ‘liking’.

Conclusion. The photographs of Aylan Kurdi became emblematic of the appalling human suffering of Europe's worst migrant crisis since the Second World War because they portrayed an unacceptable state of affairs that created a normative conflict between what is, and what should be. We show that expressing solidarity with refugees is closely intertwined with such norm violations – and solidarity is associated with communicating about the unjust harm experienced by vulnerable others.

Note

[1]His name was Alan Shenu but following Slovic, Västfjäll, Erlandsson, and Gregory (2017) we adopt the commonly used name, Aylan Kurdi.

Author Contributions

The first author developed the research concept and design, conducted data collection and analysis, and drafted the manuscript. The second and third authors provided critical revisions and conducted coding. All authors approved the final version of the manuscript for submission.

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Appendix A

Contents of Custom Dictionaries

Aylan Kurdi	Pro-refugee	Threat	Collective Action
Aylankurdi	#refugeeswelcome	harm*	act*
#Aylankurdi	refugees welcome	risk	march*
Aylan	refugee welcome	threat*	rall*
Kurdi	welcome	danger*	protest*
#Alankurdi	support for refugee*	peril*	donat*
#Syrianchild	supportforrefugee*	hostil*	support*
Syrianchild	#supportforrefugee*	menac*	campaign*
Syrian child	support refugee*	hazard*	solidarity
Syrianboy	support migrants	advers*	mobilis*
#Syrianboy	support migrant	enem*	activis*
	supportmigrants	outsider	volunt*
	supportmigrant	crisis	participa*
	#supportmigrant*	endanger*	petition*
	pray		sign-up
	#pray*		join
	shameoneurope		affiliat*
	prayforsyria*		lobby
	#prayforsyria*		recruit
	pray for Syria*		retweet
	pray for #Syria		spread
	#pray #Syria*		stand
	#pray for #Syria*		unite

#shameoneurope	persist
shame on Europe	resist*
#shame on Europe	fight
#shame #Europe	struggle*
shameoneurope	do
wehaveroom	challenge
#wehaveroom	dissent
we have room	picket*
welcome refugee*	boycott*
welcomerefugees	write-in
#welcomerefugees	demonstrat*
#withsyria	cause*
#wecandobetter	movement*
we can do better	strike*
#soukforsyria	blockade*
UK for Syria*	sit-in
solidarity	revol*
#solidarity	moratori*
#withsyria	rebel*
with Syria*	crusad*
	drive
	canvass
	persua*
	talk
	oppose

Use of an asterisk (*) at the end of the word or word stem signals LIWC2015 to ignore all subsequent letters. Consequently, for the term, 'welcomerefugee*' for example, LIWC2015 will also count the phrase: 'welcomerefugees'.

Twitter hashtags are case insensitive, but we have capitalized names to enhance readability.

Appendix B

Partial Correlations between T1 Dictionary Categories

		1.	2.	3.	4.	5.	6.
1.	Pro-refugee	–					
2.	Threat	.16**	–				
3.	Collective action	.28***	.02	–			
4.	Harm	-.01	.14**	.00	–		
5.	Anger	.07	.03	.20***	.19***	–	
6.	Risk	.16**	.19***	.38***	.27***	.21***	–
7.	Affiliation	.003	-.05	.10*	-.07	.04	.07

Correlations control for volume of tweets at T1.

**p* < .05, ***p* < .01, ****p* < .001